New developments in HPDC foundry digitalization focused on process control and ZDM

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The development of sustainable production systems focuses on minimizing production costs, increasing productivity, and improving product quality. It is universally acknowledged that digital transformation is one of the central themes of Smart Manufacturing and a necessary condition by which companies can differentiate themselves from competitors in low-cost countries. Moreover, highly flexible digital systems maintain production efficiency despite extreme variability in demand, and simultaneously enable a reduction in scrap and energy consumption. With this in mind, it is necessary to develop integrated methodologies, technologies, and tools for process control, improved maintenance, intelligent quality management, and production logistics.Against this background the new data-driven digital twin architecture of a multi-stage production system such as high pressure die casting (HPDC) interconnects all stages and their peripherals. The aim is to improve product quality towards zero defect manufacturing (ZDM) by monitoring a plant and its sub-areas to increase reliability at reduced production and maintenance costs.

Recent applications in die casting foundries highlight the expected impacts with feedback from months of production line data acquisition and management. Key elements are the flexible management of alarms and alerts as well as real-time processing of KPIs related to overall equipment effectiveness (OEE) and production costs. The project realized at RDS Moulding Technology underlines that digitalization in the foundry is an enabler for small and large companies. This article describes the design of a new sensorized mould for the production of Siemens gearmotor housings and the implementation of an intelligent monitoring system supported by a predictive quality model created through instructive sampling.

The results refer to the PreMANI project 'PREDICTIVE MANUFACTURING: design, development and implementation of Digital Manufacturing solutions for Quality prediction and Intelligent Maintenance', supported by the Veneto Region with the POR FESR 2014-2020 programme, coordinated in collaboration by the innovative regional networks IMPROVENET and SINFONET that combine industrial Internet of things (IIoT) and cyber physical system (CPS) expertise with process management and quality control along the foundry production chain.

The Smart factory and the digital twin

The Smart Manufacturing Operations Planning and Control Programme develops and implements advances in measurement science that enable standards for performance, quality, interoperability, wireless and cybersecurity in real-time prognostics and health monitoring, the control, and optimization of smart manufacturing systems (source: NIST). A Smart Factory is a complex manufacturing ecosystem where the convergence of ICT and operational technologies and skills drive digital transformation. Two challenges are emerging: the convergence of IT and operational technology systems and the broadening of the range of competencies and skills needed to drive the transformation, including cross-functional competencies, soft skills, and digital talent. The next frontier is production system efficiency rather than labour productivity. Secure data, real-time interactions, and connections between the physical and virtual worlds will make the difference: enter the digital twin (DT).

To unlock the full potential of the smart factory, organizations must design and implement a strong governance program and develop a culture of data-driven processes to make better decisions based on available, reliable, and meaningful data.

Advanced digital solutions and key enabling technologies must be constantly focused on solving the problems of the manufacturing sector, which can only return to competitiveness through:

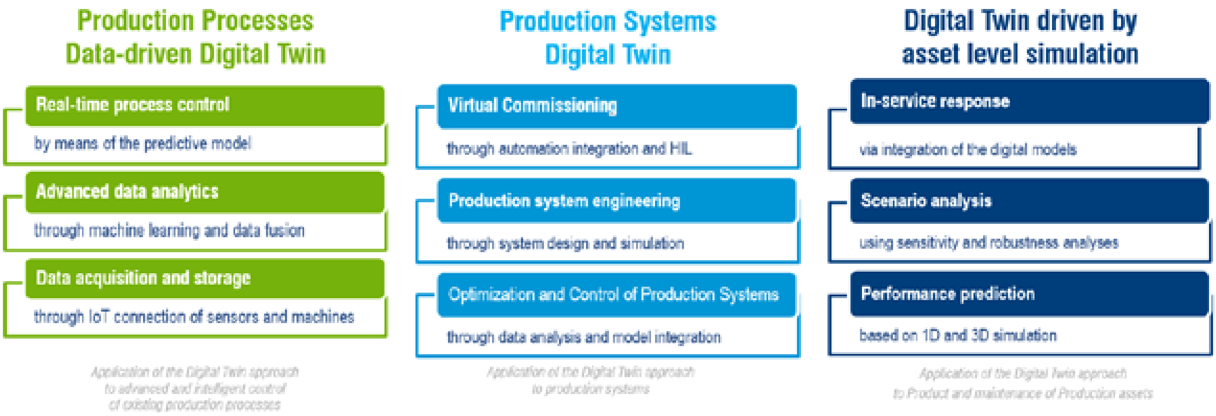

Fig. 1. The Digital Twin: (1) data-driven, (2) system modelling, and (3) simulation-powered.

- increasing efficiency,
- reducing time-to-market,
- minimizing costs, and
- increasing quality of products and services.

A data-driven digital twin of the production line

OEM specifications or supplier quality requirements partially drive product production, missing the opportunity to monitor the process and quality of any component at any stage and to react appropriately at the next stage to minimize scrap and time-to-market, while also reducing the cost of the final product. In complex production processes human input still plays a key role, mainly in supervising production KPIs and making improvement decisions. This could change as soon as effective applications of artificial intelligence enable truly automatic reconfiguration of the production system.

There are three levels of digital twin (DT): (1) data-driven, (2) system modelling, and (3) simulation-powered. This paper focuses on the first category (Fig. 1). All of them consider the three elements of real and virtual connections and human interaction.

The data-driven digital twin (DD-DT) has the macro-objective of continuously combining production efficiency (and stability) and better quality, to be achieved through digitalized production process monitoring, the interconnection of quality control and all associated data along the production chain, and the implementation of intelligent algorithms for quality prediction when total quality inspection is not sustainable. Often the two goals of production efficiency and better quality are at odds because intensive and rapid utilization of equipment can generate more breakdowns and production stoppages while better quality is only achieved with an optimized setup at each stage of the production line. The identification of the optimal setting is no guarantee of stable quality because the actual production environment (e.g. raw materials, machine, workpieces, equipment, etc.) experiences deviations in performance and time due to the dynamic behaviour of the production line. Degradation of equipment and/or machines and devices, as well as seasonal variations in the environment and environmental effects, generate instabilities in real production performance leading to stoppages and breakdowns.

More specifically, the DD-DT of the production line is based on three key elements: the monitoring platform, the data pool, and the cognitive system (Fig.2).

The monitoring platform is based on the information provided directly by the production process and its component devices, but also by advanced sensors applied to the process itself, which primarily enable the continuous monitoring of the recording of the evolution of all variables during each production cycle in order to identify all deviations from the optimal setting. Process stability means quality stability in production. At the same time, the cost estimate of the design and industrialization phases can be confirmed reliably and with process stability. Cost-benefit analysis is improved by introducing the cost model and linking it to the most relevant production parameters to verify the cost of the part number in real time.

The application of a control and cognitive system in complex production lines is not new in the factory [3-5]. The first applications

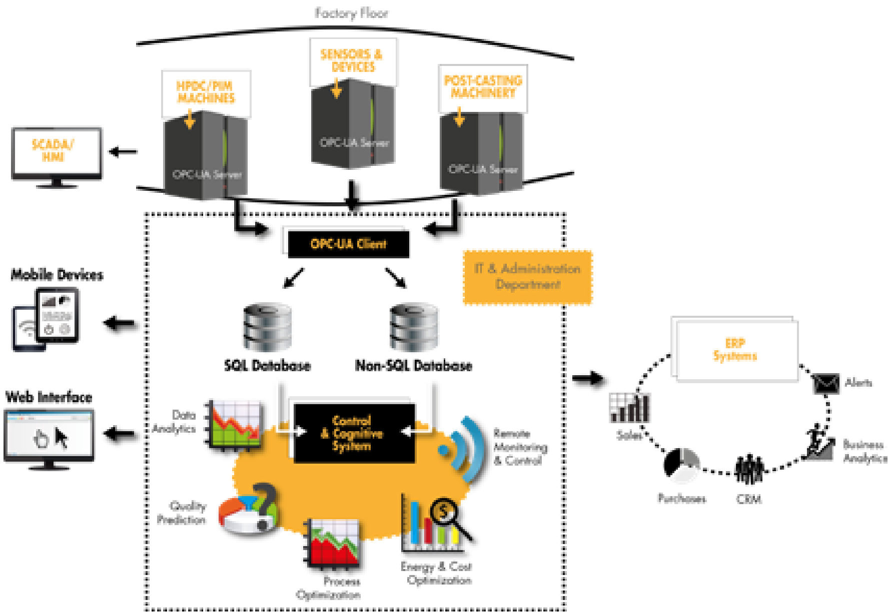

Fig. 2. Process monitoring and real-time data processing.

were in foundry and plastic injection moulding. Today, interoperability, flexibility and scalability are key elements driving innovation in the DD-DT starting from the ICT architecture. From the factory floor to the DT, the new ICT architecture activates connectivity between each manufacturer or end-user to collect data describing every stop of the production process along the production chain. Data collection is based on the OPC unified architecture (OPC-UA) protocol at the level of PLCs (programmable logic controllers) on the factory floor. The new solution is inspired by the Reference Architecture Model for Industrie 4.0 (RAMI) architecture with reference to the assets, integration, communication, information, functional, organizational and business processes.

The challenge of bringing production to zero defects requires the ability to manage the complexity of the process: identify key process variables, understand the variable-defect (cause-effect) relationship, implement sensors that can capture variables in real time, and in-depth process analysis and knowledge. Integrated virtual tools are the building blocks of the new control and cognitive platform. The rapid reconfiguration of the process for zero-defect production is supported by a deeper understanding of cause and effect based on a large and extensive amount of data from virtual and real process exploration.

High pressure die casting sector

In the smart factory scenario high pressure die casting (HPDC) of light alloys, a strategic industry for the EU, is one of the most representative large-scale production lines in the manufacturing sector in which it is possible to monitor production events with adequate precision. The process is executed by a special machine that manages a multitude of process parameters (cycle time, piston speed, mould and melt temperature, etc.). HPDC process production is one of the most 'defect-generating' and 'energy consuming' processes in EU industry. This sustainability issue requires machines and peripheral devices to be able to efficiently and ecologically support production with higher quality, faster delivery times, and shorter lead times between successive generations of products.

Lack of quality significantly affects the cost of transformation, and defects are often detected long after production, without taking real-time, corrective actions based on a continuous learning model that links process data input to potential defects. The real limitations on the HPDC industry are the continuously increasing costs that reduce efficiency and minimize the impact of innovations and development. Furthermore, standard products such as gearboxes and motor blocks will soon be replaced by large thin parts required for electro-mobility. These parts are extremely difficult to produce reliably with high quality and represent a challenge for the HPDC industry.

The new DD-DT platform covers the full HPDC production chain from material processing to the final product. The major limitation is the acquisition of data from each stage, as well as the corresponding digitalization and classification of defects.

HPDC is a typical production process that suffers greatly from the problem of low yields. It generates defects of various kinds and types with an average rejection level of 10%. These defects are classified in CEN TR 16749 [2], considering a three-level approach. A survey of EU HPDC foundries found that most foundries quantify defects by considering gas/air porosity (70.9%) or shrinkage (56.4%) using X-ray inspection (in the range of 70-80% of cases). However, in certain situations these types of defects in castings can be accepted if they fall within a previously identified threshold (in this case, and according to the EN 12258-1 definition, they are considered 'imperfections' instead of 'defects').

The foundry use case

A gearmotor housing was selected as a use case in which to apply all the advanced and innovative solutions for optimizing and monitoring the HPDC process. The housing is produced from a net-shaped geometry with one part per die and assembled into an electric motor for various applications such as escalators (Fig. 3).

The die and related process parameters was optimized using the casting simulation tool (MAGMAsoft). It was necessary to first optimize the mould, modifying the gait and overflow systems to improve the fluid dynamics in the cavity and to redesign the thermoregulation and lubrication systems in the cycle to improve the thermal performance of the equipment. At this stage, automatic optimization techniques were applied to define the best configurations.

This activity was also preparatory to defining the positioning for the thermal and pressure sensors on the printing parts. Subsequent to the mould redesign and using virtual simulation it was possible to identify the macro areas on which to apply the sensors and to define which of these areas would be more sensitive to process variations. The purpose here was to define the most important areas from which to capture process instability data to be correlated with the quality of the components produced.

The position of the sensors was chosen by analysing virtual DOEs (design of experiments), where the process parameter variables include:

- injection curve (first phase speed, second phase speed, and switching point)

Fig. 3. High pressure die casting product: a gearmotor housing.

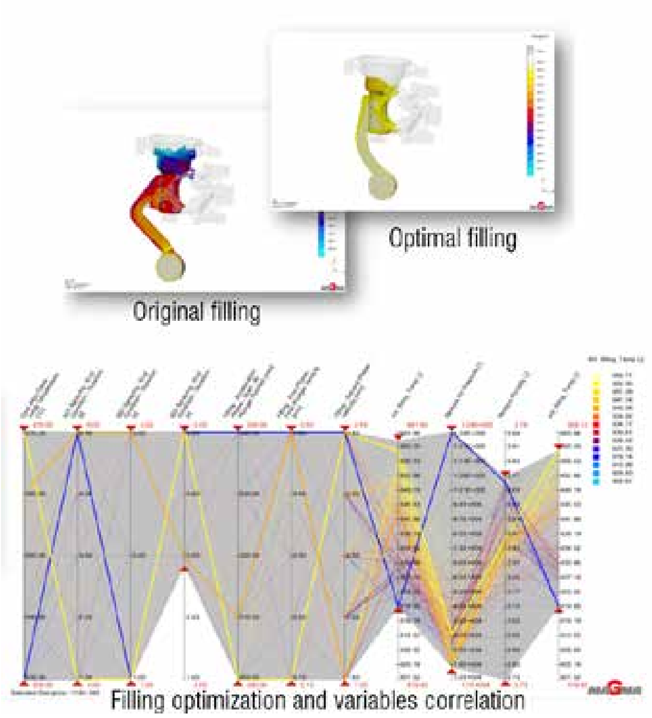

Fig. 4. Optimization of filling and correlation of variables with defects.

- lubrication time and blowing time
- temperature and flow of the temperature control units
- alloy temperature

The variations in these variables is observed and correlated with both the values emitted by the sensors and the previously presented component quality criteria by means of appropriate processing tools (Fig. 4).

New revised castings were studied to improve castability and quality: from a fluid dynamics point of view, changes to the geometry and optimal parameter configurations are suggested.
Fig. 5 shows how porosity was significantly reduced and die life was extended by changing the thermoregulation and lubrication configurations (see Table 1).

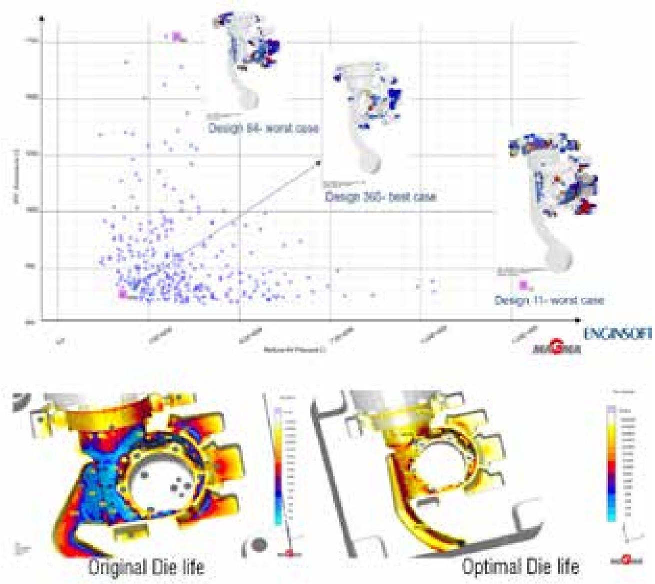

Fig. 5. Optimization for solidification defects and prediction of die life.

Original HPDC parameters	Optimal HPDC parameters
Oil at 180 °C for mobile die thermoregulation	Oil at 130 °C for mobile thermoregulation + H2O at 20 °C in central die-core
Oil at 250 °C for fixed thermoregulation	Oil at 130 °C for fixed die thermoregulation
Die lubrication for 15 sec with an average local time of 2 sec	Die lubrication in three steps Step 1: 3 sec; step 2: 2 sec; step 3: 5 sec

Table 1. Thermoregulation and lubrication configuration

Process monitoring and alerts

After the design phase, the monitoring platform was implemented by integrating the process and equipment data collected from an intricate network of existing and innovative sensors that had been applied to all key units in the manufacturing production line. The platform performs real-time data mining and triggers alerts when a deviation is outside the optimal range.

With regard to monitoring, data was acquired from the measurement system (supplied by Electronics GmbH) connected to a 560-ton press (Table 2).

HPDC PHASE	SENSOR SIGNAL	RDS APPLICATION
Injection	Biscuit thickness Length of injection phases Injection force First stage pressure Injection pressure Exhaust pressure Specific pressure Piston position	Piston position Injection pressure Exhaust pressure
Solidification	Contact temperature Contact pressure	Contact temperature Contact pressure
Cycle preparation	Oven temperature Room temperature Lubricant quantity	Oven temperature Room temperature Lubricant quantity

Table 2. Data acquisition from the measurement system

Predictive quality model

Standardized quality classification and investigation methods [1], and the traceability of parts, are crucial for training the predictive quality model that guides the minimization of the indices affecting rejection rates. All process parameters (both virtual and physical) that can influence the quality of a given product were considered in the DOE used to train metamodel by correlating the process input variables and sensor data with the quality indices for the areas of interest.

Full factorial and Sobol algorithms were applied to the DOE of the housing which is produced in 344 shots considering statistical repeatability and thermal steady state. The correlation of the input signal and quality indices highlights the most significant variables and deviations affecting the quality in the specific stage of casting, e.g. the die pressure signal correlates well with porosity and cold shot in the central areas of the body.

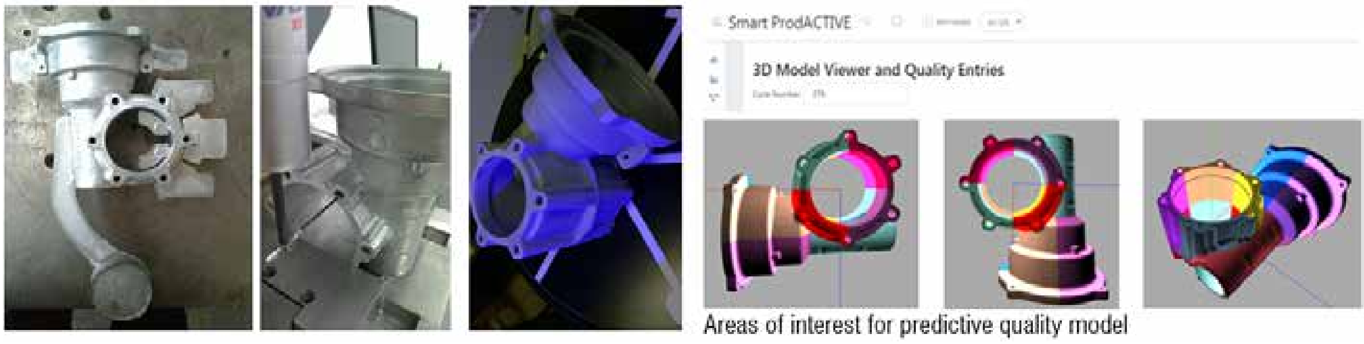

Fig. 6. Quality control and casting area of interest.

Quality mapping is based on NDT (non-destructive testing) using visual inspection, X-ray, and metrology tools. Defect classification and digitalization is required for all the different areas of interest (Fig. 6) with particular reference to joint or cold shot, internal porosity, and lamination.

The quality prediction model correlates process variables with quality indices to supervise and optimize process parameters to result in zero defects. The cognitive system works with advanced machine learning algorithms to support the reactive decision-making in real time to improve product quality by catching potential defects as early as possible during key process steps. A wizard guides the user during the training phase. The system also offers a set of ready-to-use machine learning (ML) algorithms, automatically processes all data sources to obtain the optimal approximation, and displays the processing results. The algorithms are used together with enhancement techniques based on: (a) decision trees, (b) nearest neighbours, (c) random forest, (d) support vector machines, and e) neural networks or customized algorithms.

Users do not need analyse the data or manually find the model or algorithms for their production scenario. A simple interface guides them in acquiring, interpreting, and classifying the production signal in the dataset to train the metamodel, and in verifying the correlation, accuracy and error metrics. After automatically training the metamodel via grid search (cross validation), a single model was generated for each area and different defect. An example of error is 9.6% for porosity in the central body in contact with mobile die. The algorithms and models are automatically improved and retrained during production using the results of the new quality inspections.

DD-DT-assisted production and predictive quality modelling

Production normally starts using the best process configuration. The stability and repeatability of the best cycle is monitored with real-time comparisons to the previously selected reference curve and using instantaneous verification of the thresholds to meet the predicted quality. The waste or good parts predicted by quality models are displayed on a PC, table or smart phone connected to the system via the web. The decision support system (DSS) supports the selection of the best setting for the reconfiguration of the process parameters by suggesting the correct adjustment. It sends a message to the operator containing the identified defects and a proposed new configuration. The GUI displays the deviation recovery, process stability, and good quality forecast. At the same time, it updates costs and production KPIs in the OEE (Figs. 7-8). The basic dashboard includes some predefined KPIs, such as quality, availability, and target cycle time. The user can define new KPIs (e.g. material volume, energy savings, and cost).

The results widget (Fig. 8) assists the quality prediction system: when the defect index values for a casting are all below the relevant thresholds set, the part is considered 'good'; if even one value is over the threshold, the part is considered a 'waste'.

The monitoring system controls the quality of the production process from an abnormal operating state that generates waste (i.e. during the heating phase), to the expected operating state that produces good parts.

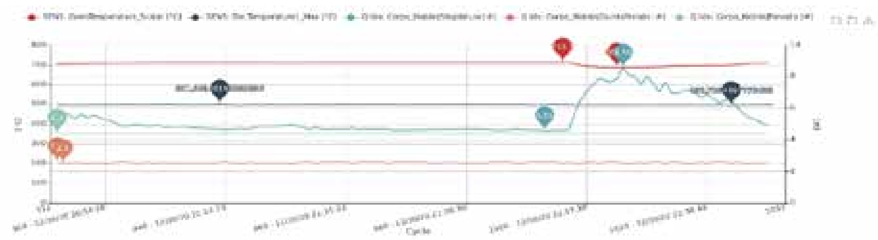

Fig. 7. Example of KPI display during production.

Fig. 8. Identification of good/waste castings (left) and list of defect levels in the corresponding areas (right).

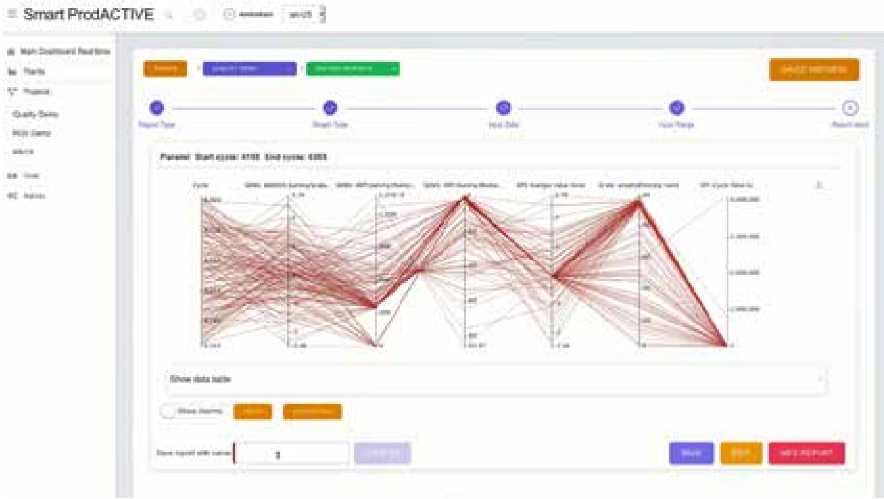

Fig. 9. Parallel chart of process parameters-defects correlation in a set of 150 cycles.

In the end, the monitored data also contributes significantly to the real-time costing of each part. The cost model is based on the production and organization phases and the assigned cost categories (e.g. materials, manhours, maintenance, etc.) and cost items (e.g. raw material, scrap, operator, etc.). The cost KPI is evaluated after each shot in real time and the historical database shows the trend by correlating it with the process parameters and quality levels. The report wizard guides the user in selecting the chart type, data, and the cycle interval to be displayed. The periodic reports that can be printed and automatically shared with managers can include any graph or table (Fig. 9).

The repository of reports and data tables sits in the cloud and the MES (manufacturing execution system) connection was tested.

Conclusions

This paper discusses a significant improvement to sustainable production when there are limitations to non-destructive inspections in-line (e.g. in casting) by means of an improved inspection system that enables a 'right first time' production process. Newly developed methodologies and tools prevent defects from being generated at the component level and propagated to the system level. A digital twin substantially improves and virtualizes manufacturing and engineering processes to save resources by avoiding testing and mock-ups.

The data-driven digital twin has proven to be essential in smart factories (e.g. Foundry4.0). The new, distributed architecture and extension of the interoperable, flexible digital platform along the production chain:

- facilitates remote process control supported by alarm management to accelerate rapid identification of defects up to full zero-defect production,
- reduces the cost of non-quality, and
- enhances the ability of agile production to restart with corrected configurations based on digital know-how.

The pilot line of this new development in foundry digitalization demonstrates a significant reduction in defects with a 50% reduction in HPDC waste and a 60% increase in die life. The simulation of the foundry process supports the design of highly sensitive sensor network to detect process instability and capture defects in real time. Production supervision alerts the user in case of deviations and suggests the appropriate action based on the predictive quality model.

This validation in the foundry environment is also a reference for other complex manufacturing processes where the same approach can be successfully applied. The web platform has been designed to support multi-site production line monitoring (e.g. material supply, casting, heat treatment, and machining in the case of a foundry).

The cloud becomes the final repository of the reports and data tables and the MES connection was tested.

The digital twin is enhanced by real-time monitoring, data collection, and artificial intelligence to train the predictive model that is implemented from the machine level up to production chain level. This represents a significant step forward towards the most complete of digital transformations enriched by advanced ICT and human decision-making systems based on data, simulations, and representative process and product KPIs.

References

[1] E. Gariboldi, F. Bonollo, P. Parona, 'Handbook of defects in HPDC'. AIM, Milano (2010).

[2] CEN T/R 16749: Aluminium and aluminium alloys — Classification of defects and imperfections in high pressure, low pressure and gravity die cast products, CEN, Brussels (2014).

[3] F. Bonollo, N. Gramegna, 'The MUSIC guide to the key-parameters in high pressure die casting', Assomet Servizi srl, EnginSoft SpA, ISBN 978-8887786-10-1, 2014.

[4] F. Bonollo, N. Gramegna, 'Smart control and cognitive system applied to the HPDC Foundry 4.0' Assomet Servizi srl, EnginSoft SpA, ISBN 978-8887786-11-8, 2016.

[5] F. Bonollo, N. Gramegna, 'HPDC foundry competitiveness based on smart control and cognitive system in Al-alloy products', HTDC 22-23 June 2016, Venice (Italy).

[6] L. Macchion, G. Kral, F. Bonollo, N. Gramegna, 'Application of cost model approach in HPDC contexts', HTDC 22-23 June 2016, Venice (Italy).

[7] B. Kujat, N. Gramegna, M. Benvenuti, 'Innovative control and real-time quality prediction for the casting production of aluminium alloy structural components at AUDI AG', HTDC 22-23 June 2016, Venice (Italy).

[8] N. Gramegna, F. Bonollo, G. Greggio, 'Digital transformation to Foundry 4.0', 73WFC, 25 September 2018.

[9] L. Ansberg, F. Bonollo, N. Gramegna, 'Twenty years of research projects targeted to zero defect manufacturing in diecasting', 73WFC, 25 September 2018.

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